Enhanced Reconstruction of Architectural Wall Surfaces for 3D Building Models

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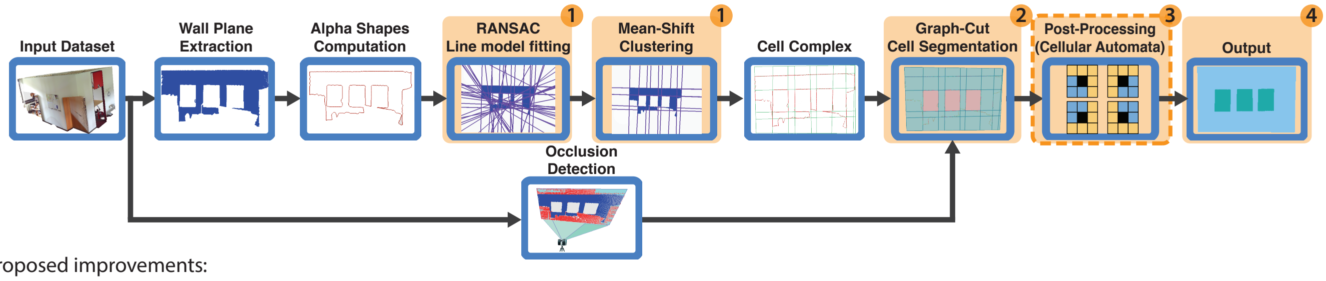
Introduction

Due to recently increased demands for semantically rich 3D Building Information Models (BIMs), the accurate recovery of building's architectural permanent elements is of high importance. For real-life projects, the highly added value in BIMs is originated, not only from the building's architectural shape, but mainly from the fine architectural details derived e.g. from its wall elements. In this work, we focus on reconstructing the fine architectural details of buildings, such as the windows and doors, and make specific interventions to state-of-the-art [1] which allow better reconstruction results under severely occluded wall surfaces, automatic semantization and extended applicability.

Proposed Improvements

Wall surface reconstruction pipeline, as presented in [1]:

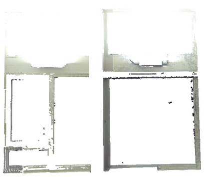


Proposed improvements:
1. We replace the line model fitting and clustering approach.
2. We add a new regularization term in graph-cut segmentation approach, enforcing spatial consistency.
3. We introduce a highly efficient post-processing stage for refining the wall surface segmentation.
4. We annotate the reconstructed wall elements, enriching the final results.

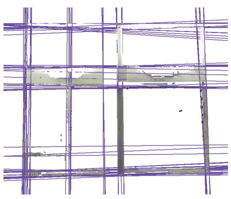
Wall Surface Reconstruction

Our pipeline takes as input the architectural shape of the indoor environment, extracts its wall surfaces and computes the α-shapes 2D polytope of their points, following the approach in [1]. Next, a line model fitting method is applied to α-shapes boundaries for getting regularized boundaries. Due to the inherent uncertainties introduced by the structural composition of the α-shapes, RANSAC will not produce the most optimal results. Thus, we use the PEARL multi-line model fitting method [2], which combines model sampling from data points as in RANSAC but using iterative re-estimation of inliers.

Next, to favor alignment with the wall elements and reduce the complexity of wall surface partitioning, we replace Mean-Shift used in other methods [1, 3] and propose a robust and feature-preserving line clustering technique, in which each line model is associated with a weight derived by the number of α-extreme points that contributed to its estimation. Line space partitioning takes place by considering the maximum distance between the neighboring lines and the maximum angle of their normals, evaluating all lines through a voting process inside a local neighborhood. The line that approximates better the local geometry is set as the mode line in the neighborhood.



Extracted wall surface.

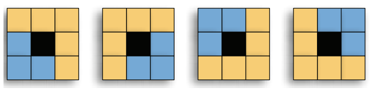


Representative mode lines.

Similar to [1], we perform in the next step occlusion detection, while in the graph-cut segmentation stage we enforce spatial consistency between neighboring cells introducing to the n-links a new regularization weighting term for lowering the cost of adjacent cells that are expected to belong to similar regions.

Post-Refinement and Semantization

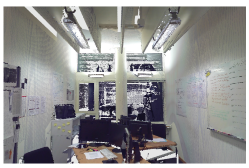
To enhance further the reconstructed results and eliminate the erroneous cell classifications under extremely cluttered or occluded environments in the cell complex segmentation stage, we propose a post-refinement step which relies on the contextual information of the cells. Cellular Automata (CA) [4] were used for this purpose, operating on the cell complex of the wall surface. Considering the Moore neighborhood with radius **r** = 1 and the following CA rule patterns, we evaluate certain criteria (e.g. point density, cell label and total number of points) and replace the central cell's label by a neighboring label if the CA rule criteria are fulfilled.



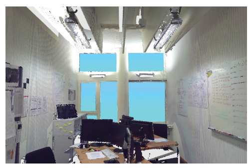
CA rule patterns.

In the last stage of our pipeline we semantically annotate the segmented wall elements based on contextual and geometric cues. Each wall element is evaluated against certain shape and positional criteria and gets a specific label from the label set {*window*, *door*}.

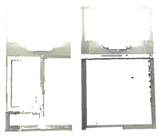
Results



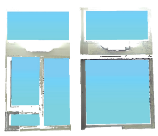
Input point cloud.



Final point cloud.



Extracted wall surface.



Semantically reconstructed wall openings.

References

[1] G.-T. Michailidis and R. Pajarola: Bayesian graph-cut optimization for wall surfaces reconstruction in indoor environments. The Visual Computer 33, 10 (2017), 1347–1355.
[2] H. Isack and Y. Boykov: Energy-based geometric multi-model fitting. International Journal of Computer Vision 97, 2 (2012), 123–147
[3] S. Ochmann, R. Vock, R. Wessel, R. Klein: Automatic reconstruction of parametric building models from indoor point clouds. Computers & Graphics 54 (2016), 94–103.
[4] J. Von Neumann: Theory of Self-Reproducing Automata. University of Illinois Press, 1966.

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